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Poor Areas, Or Only Poor People?

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Instead of targeting poor areas, should poverty programs target households with personal attributes that foster poverty, no matter where they live?
Maybe not, these results suggest.

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Summary findings

Instead of targeting poor areas, should poverty programs target households with personal attributes that foster poverty, no matter where they live?

Possibly not. There may be "hidden" constraints on mobility, or location may reveal otherwise hidden household atributes.

Using survey data for Bangladesh, Ravallion and Wodon find significant and sizeable geographic effects on living standards, after controlling for a wide range of nongeographic characteristics of households, as would typically be observable to policymakers.

The geographic effects are reasonably stable over time, robust to testable sources of bias, and consistent with observed migration patterns.

Poor areas are not poor just because households with readily observable attributes that foster poverty are geographically concentrated. There appear to be sizable spatial differences in the returns to given household characteristics.

Their results reinforce the case for anti-poverty programs targeted to poor areas even in an economy with few obvious impediments to mobility.

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Poor areas, or only poor people?

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1 Introduction

Every country has its "poor areas"-places where the incidence of poverty is unusually high by national standards. Governmental and non-governmental agencies have devised various programs to target extra resources to these areas, with the aim of reducing poverty.[2]

However, the case for targeting poor areas is not obvious in a setting in which there are no evident barriers to migration. Suppose that households can freely choose their location; we can term that state of affairs "free migration". If the economy is in equilibrium, such that nobody wants to move, then standards of living must be completely determined by mobile non-geographic household characteristics. For if geographic location were to have an effect on consumption after controlling for those characteristics, then households would move to the areas with positive geographic effects. An unusually high poverty rate in some area would still be possible in equilibrium, through a spatial concentration of households with poor characteristics. But, as long as it was possible to target according to non-geographic characteristics, there would be no point to geographic targeting. Attempts to redistribute between rich areas and poor areas would generate migration until a new equilibrium is restored, consistent with the new distribution of non-geographic attributes. There would be no point using residential location as an indicator for targeting anti-poverty schemes.[3]

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[2] For an overview of past uses of geographic targeting as an anti-poverty policy in developing countries see Lipton and Ravallion (1995, section 6). Discussions of the case for such targeting have assumed that migration is restricted and viewed place of residence as a poverty indicator, albeit an imperfect one (see, for example, Ravallion, 1993).

[3] There may still be an efficiency case for poor-area programs when regional governments supply public services. Without appropriate inter-regional transfers, free migration between the regional jurisdictions does not, in general, imply efficient local provisioning (Flatters, Henderson and Mieszkowski, 1974; Atkinson and Stiglitz, 1980, Chapter 17). It is however unclear whether the optimal transfers would resemble

This argument against poor area policies may, however, overlook some important features of the real world. Two stand out. Firstly, there may be constraints to achieving a free migration equilibrium in practice. Impediments to migration can take many forms. Typically, there are very few governmental restrictions on internal migration, although both geography and cultural-linguistic diversity can remain real constraints. But even without obvious social, physical or governmental impediments to internal migration, moving can be a costly and risky venture for poor people. Local personal ties of patronage or indebtedness, imperfect information, lack of access to credit or insurance, and even small but (to poor people) significant costs of moving can all entail that a country in which migration is "officially" unrestricted may still be a long way from the equilibrium to be expected with free migration. Poor area programs then make more sense. Strong geographic effects on living standards for similar households may exist and persist over (possibly considerable) time. This is not inconsistent with migration, which may well be a slow "disequilibrium" process of adjustment to the very existence of geographic effects.

Secondly, there may be constraints on the ability of policy makers to target household characteristics when attempting to reduce poverty. This leads to another argument for geographic targeting even in settings in which mobility is unrestricted. Standards of living may be completely determined by mobile non-geographic characteristics of households, but a significant subset of these characteristics are unobserved by policy makers and are spatially autocorrelated as a result of a sorting process through migration. The key question for policy is then the quantitative

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a "poor-area program". Also, there is nothing to stop the local governments from making the transfers themselves, and behaving strategically. Then the Nash equilibrium with free migration will be efficient without central intervention (Myers, 1990); this also holds when there are inter-jurisdictional spillovers (Wellisch, 1993).

importance of the geographic effects which cannot be attributed to the household attributes observable by policy makers.

We examine these issues empirically, using data for Bangladesh. It is known that there are large spatial differences in levels of living in Bangladesh. Yet, there are no administrative impediments to internal migration and few physical ones, since the country is spatially contiguous, with over 120 million people living in an area roughly the same as that of England or Florida. Nor is it plausible that there are significant cultural barriers to internal migration. The vast majority of the population share the same ethnicity, language and religion.

We show, however, that sizable geographic differences in living standards in Bangladesh persist when one takes account of the spatial concentration of households with readily observable non-geographic characteristics conducive to poverty. The same, observationally equivalent, household is poor in one place but not another. Moreover, these geographic effects appear to be stable over time. Differences in measurable non-geographic household characteristics do account for a share of the differences in living standards, and there could well be some omitted household attributes, which may be spatially correlated and so bias our estimates of the pure geographic effects. However, our results indicate that the geographic differences in living standards cannot be readily attributed to differences in non-geographic household characteristics. Indeed, where you live appears to be independently important, and very important quantitatively, in explaining poverty in Bangladesh.

The following section presents our tests for geographic effects on living standards. Section 3 discusses some possible sources of bias in our results. The presence and implications of the identified geographic effects are discussed in section 4. We conclude in section 5.

2 Testing for geographic effects

The arguments for and against geographic targeting discussed in the introduction rest in part on an empirical question: are there geographical effects on living standards after controlling for observable non-geographic characteristics of households?

To address that question, we use the micro-data from two comparable cross-sectional surveys for Bangladesh three years apart. Using two surveys allows us to check robustness of geographic effects over time to spatially correlated measurement errors, as long as these are independent over time. With these data we estimate regression models for real consumption, defined as nominal consumption deflated by a regional-specific poverty line incorporating spatial cost of living differences facing the poor in Bangladesh. The models include a reasonably wide range of measurable household characteristics as controls for identifying geographic effects. Nonetheless, there may be biases due to omitted household characteristics which are spatially correlated. We provide tests for robustness to the specification of the set of household characteristics and also a test for possible sample-selection bias due to rural-urban migration.

To analyze the determinants of consumption, we estimate separate regressions for each of the urban and rural sectors using two sets of household sample data, denoted U and R for urban and rural areas respectively. To measure real consumption C we deflate nominal consumption by a date and area-specific poverty line (discussed below). We assume that logC is a linear function of a $k\times1$ vector of observed non-geographic variables (X) and a $m\times1$ vector of locational dummy variables (D). The function differs between urban and rural samples:

$$\log C_i = \alpha_U + \beta_U'X_i + \delta_U'D_i + \varepsilon_{Ui} \qquad (i\in U) \qquad (1)$$

$$\log C_i = \alpha_R + \beta_R'X_i + \delta_R'D_i + \varepsilon_{Ri} \qquad (i\in R) \qquad (2)$$

where $\alpha_{U,R}$, $\beta_{U,R}$ and $\delta_{U,R}$ are 1×1, $k\times1$ and $m\times1$ vectors of parameters and the error terms ($\varepsilon_{U,R}$) are each independently distributed with zero mean. The vector X_i includes:

• Demographics: numbers of babies, children, and adults (plus their squared values); household structure (head with a spouse, head without a spouse and married, etc.,); sex of the head; age of the household head and its square; religion of the household (Muslim or non-Muslim).

• Education: the education level along four categories of the household head, of his spouse, and the difference between the highest education level in the household and the maximum of the education level of the head and the spouse (or of the head only when there is no spouse).

• Land owned: the household's land owned in four categories depending on area.

• Occupation: the household head's main occupation (twelve occupational classifications were used: five agricultural, six non agricultural, and one for non working heads).

The data are the 1988/89 and 1991/92 Household Expenditure Surveys of the Bangladesh Bureau of Statistics (hereafter BBS). The two surveys are independent, but otherwise used virtually identical methods (in the sampling, questionnaires, and processing). These data are appropriate for the task at hand: one of their main stated objectives is to monitor consumption and poverty in the country. The surveys provide detailed information on the expenses of each household. A few non recurrent expenses for ceremonial activities (marriage, death) have been netted out of the consumption aggregate. After data cleaning, the two survey rounds cover respectively 5626 and 5725 households. Two variables can be used to define the geographic location of households. We know if the households live in urban or rural areas, and we know to which of 17 districts each belongs.[4] The combination yields 34 "areas", 17 rural, 17 urban.

Consumption is normalized by a poverty line giving the estimated cost of living in the area where the household lives. The poverty lines are based on a well-defined food bundle that has been widely used in poverty measures for Bangladesh; this meets predefined daily nutritional requirements. Next, we used the survey data to estimate for each year and each area the price of the items in the food bundle, controlling for household characteristics in order to capture the price paid by the poor. (The unit values from the survey were purged of differences in product quality; see Wodon, 1996). Finally, given that prices for non-food goods are not available, we estimated for each year and each area an allowance for non-food consumption; this was equal to what the households whose total expenditure is equal to the cost of the food bundle are expected to spend on non-food items (Ravallion, 1994). Note that this yields a relatively low allowance for non-food consumption since it is based on what households who do not meet their nutritional requirement spend on non-food items. Given that these households only have enough to meet their basic food needs, we can assume that the allowance for non-food expenses covers (at best) bare essentials. Summing up the allowances for food and non-food consumption yields the total poverty lines by year and by area. We computed 14 area-specific poverty lines for each of the two survey years;

[4] There are three types of urban area identified in the data. However, because of smaller sample sizes, we aggregated all urban strata together. There are officially 20 "Greater Districts". However, for one district (Chittagong Hill Tracts), no observations were available. Two additional districts (Jamalpur and Patuakhali) have no observations corresponding to urban households. These two districts were aggregated with contiguous districts of a similar level of development. We thus have in total 17 greater districts. If the sample sizes were sufficiently large, in order to test for structural changes in parameter estimates across districts and urban/rural areas, we could ideally run 34 separate regressions for the urban and rural areas of our 17 districts. In practice, due to our limited sample sizes, we estimate regressions for the urban and rural sectors only.

details can be found in Wodon (1996).[5]

Our estimates of the regressions (1) and (2) are in Table 1. The standard errors use the Huber-White correction for heteroscedasticity. The following observations can be made:

• Different models are determining consumption in urban and rural areas. The null hypothesis that all coefficients are the same in both equations is rejected at the one percent level. Table 2 gives the test results. Looking at subsets of household characteristics, the hypotheses that the coefficients are the same are also rejected at the one percent level for all subsets of variables except for the constant, household size, and the other demographic/religion variables.

• There are a number of significant demographic effects in both sectors. Chief among them is household size: the larger the household, the lower its per capita consumption.[6]

• There are significant gains from education. This holds in both urban and rural areas, though the proportionate consumption gains from extra schooling are higher in urban areas.

• More land yields significantly higher consumption in both urban and rural areas.

• There are also significant differences associated with occupation; all occupation groups are better off than landless agricultural workers.

• There are significant differences in consumption between districts, and between the rural and urban areas of given districts, after controlling for the above household characteristics.

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[5] Due to small sample sizes and to the estimation requirements, we had to aggregate the 34 areas into 14 greater areas to compute the poverty lines for each of the two survey year. The computation of poverty lines for these 14 areas is the best that can be done with the available data to control for price differences. It is an improvement over the common practice of computing only two poverty lines, one for urban and one for rural areas.

[6] The welfare interpretation of this finding is questionable. The effect of household size could reflect an error in measuring welfare, in that scale economies in consumption within households have been ignored (Lanjouw and Ravallion, 1995).

3 How robust are our results?

There are good reasons to be skeptical of the above results. With the data available, we cannot alleviate all possible concerns, but we can address some.

3.1 Selection bias

The existence of rural-urban migration suggests that place of residence may not be exogenous. To test for this source of bias we estimated the following version of the standard switching model.[7] In addition to equations (1) and (2) we have:

$$I_i^* = \alpha_C + \log G_i - \gamma_c' W_i + \varepsilon_{Ci} \tag{3}$$

where $I_i = 1$ if $I_i^* > 0$ and $I_i = 0$ if $I_i^* \leq 0$. Equation (3) gives the net gain (or loss) I_i^* to living in an urban area rather than a rural area. This is a function of the real per capita consumption gain (log G_i), minus any cost of living in an urban area not already included in the estimates of the poverty lines and represented by $\gamma_c' W_i$. Although we do not observe this net gain or loss, we observe the decision by each household to live in an urban (I_i=1) or a rural (I_i=0) area, as well as its resulting real per capita consumption. Substituting (1) and (2) in (3) yields the reduced form equation for the switching regression:

$$I_i^* = \alpha_C + (\alpha_U - \alpha_R) + (\beta_U - \beta_R)' X_i + (\delta_U - \delta_R)' D_i - \gamma_C' W_i + \varepsilon_{Ci} \tag{4}$$

Let ψ_i denote the fitted values of I_i^*, and let ϕ and Φ be the density and cumulative density functions of the standard normal. The conditional means of the disturbances in (1) and (2) are $E[\varepsilon_{Ui} | I_i = 1] = \sigma_{UC}\, \phi(\psi_i)/\Phi(\psi_i)$ and $E[\varepsilon_{Ri} | I_i = 0] = \sigma_{RC}\, [-\phi(\psi_i)/(1-\Phi(\psi_i))]$, where σ_{UC} and σ_{RC} are the covariances between the error terms of the two consumption equations (1)-(2) and the error term

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[7] There are a number of expositions, including Maddala (1983, Chapter 9). An early application to migration was Nakosteen and Zimmer (1980).

of the switching equation (3). This yields:

$$E[\log C_i \mid I_i=1] = \alpha_U + \beta_U'X_i + \delta_U'D_i + \sigma_{UC}\,\phi(\psi_i)/\Phi(\psi_i) \qquad (5)$$

$$E[\log C_i \mid I_i=0] = \alpha_R + \beta_R'X_i + \delta_R'D_i - \sigma_{RC}\,\phi(\psi_i)/[1-\Phi(\psi_i)] \qquad (6)$$

With sample selection the estimates of σ_{UC} and σ_{RC} should be statistically significant. To estimate σ_{UC} and σ_{RC}, the usual two-stage procedure involves first estimating the reduced form (4), and then estimating (1) and (2) using the Mills' ratios computed from (4).[8]

With our set of regressors, the estimates of σ_{UC} and σ_{RC} were not significant. There was no sign of selection bias. This also held for a number of ad hoc alternative specifications. The test thus suggests that we can make use of parameter estimates from the urban and rural regressions without worrying about sample selection bias.

However, this test relies on a number of assumptions which highlight the difficulty of conducting the selection test. The first set of assumptions involves implicit restrictions on the migration process and occupational choice. Including the geographic dummies in the urban and rural consumption regressions and using the above specification for the switching equation implicitly restricts migration from rural to urban areas to take place within the same district. This is because in the switching equation, the net gain from living in urban or rural areas is district-specific for any given household due to the inclusion of the term $(\delta_U - \delta_R)'D_i$. The gain to moving from one

[8] If we were interested in the structural equation (3.1), we could use the predicted values from (2.1) and (2.2). To do so, we should have variables in W not included in X and D. While this identification condition may seem innocuous, it is not straightforward to find variables which affect the location decision of households but not their real per capita consumption. In the literature on switching models, identification has often been obtained by excluding one or several variables from the consumption regressions or by using different expressions of similar variables in different equations (such as years of schooling in one case and degree obtained in the other). For us, because we do not find strong evidence of sample selection and because of the difficulties to be discussed below, we need not estimate the structural equation, so that the solution to the identification problem is of less concern.

district to another cannot be factored in. If we had migration information in the data, we could solve the problem by assigning to a household leaving a rural area of district j for an urban area of district k the corresponding gain $\delta_{Uk} - \delta_{Rj}$. In the absence of migration information, we are left with the choice between implicitly restricting migration to take place within districts, or not taking into account sectoral effects within districts in the switching equation. The first alternative is not supported by the facts. Using the 1991 census, BBS (1995a: 46, Table 3.5) found significant migration between districts and larger administrative divisions.[9] The second alternative is not supported by the facts either, since geographic effects appear to be significant and consistent with observed migration (as discussed further below, areas with favorable geographic effects such as the urban areas of the Dhaka district are also those with large immigration). Note that similar reasoning can be applied to the occupation dummies. The presence of the occupation terms in $(\beta_U - \beta_R)'X_i$ in the switching regression assumes that when households decide to live in urban versus rural areas, they do not consider changing occupation. Again, this is unrealistic since most households leaving rural areas give up their agricultural jobs to take on non agricultural jobs in urban areas.

The second set of assumptions involves endogeneity problems. Some urban households may have better educated members because they live in urban areas, rather than choosing to live in urban areas because they have better educated members and the returns to education are greater

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[9] Given that the Dhaka SMA is by far the largest urban area in the country, and given that in percentage it has grown faster than most other urban areas (except the Rasjhahi SMA), we could assume for simplicity that the migration to the urban areas of the Dhaka district accounts for most of the exodus from rural areas. With this assumption, we could estimate the above switching regression model with the choice of location being the Dhaka SMA in the first equation, and all other areas in the second. Again, when doing so, we did not obtain significant estimates for the coefficients of the Mills' ratios.

there. Similarly, some households may have more land because they live in rural areas, rather than choosing to live in rural areas because they have more land and the returns to land are greater there. The potential endogeneity of household characteristics also applies to demographic variables if, for example, location affects the number of children in a household rather than the other way around. Under such endogeneity, the switching model would be miss-specified.

For these reasons, our results rejecting selection bias must be deemed at best suggestive.

3.2 Measurement error in the cost-of-living deflators

Welfare-measurement errors related to household (non-geographic) characteristics will not bias our estimates of geographic effects. If, for example, the use of a "per capita" normalization does not deal adequately with economies of size in household consumption or demographic differences in consumption needs then this will be picked up by the demographic variables on the right hand size. This alters the welfare interpretation of those variables, but does not bias our estimates of the geographic effects.

However, the method of adjusting for spatial cost-of-living differences is more worrying. We may observe significant geographic effects because of measurement errors in the poverty lines used for adjusting nominal consumption to differences in costs of living between districts. Specifically, while our food poverty lines may be assumed to track differences in costs of living reasonably well, our estimates for the non-food component of the poverty lines may be off-track since they are not based on observed differences in prices for similar goods. To check the robustness of our estimates to alternative methods, we computed a second set of poverty lines entailing larger allowances for non-food consumption. The non-food component for an area was defined as the mean non-food spending of households whose food (rather than total) consumption equals the food poverty line. At this point, households spend more on non-food items that when total consumption is equal to the food poverty line. The differences between the poverty lines by district are also larger. The second set of poverty lines yields lower levels of real consumptions, but the results in terms of district coefficients are not affected. The correlation between the coefficient estimates of the district dummies using the two sets of poverty lines is 0.88 for the urban regressions, and 0.98 for the rural regressions. The levels of significance are virtually unaltered.

What would it take to nullify the effects of all dummy coefficients in the urban and rural regressions? Because poverty lines are geographically defined and geographic dummies are included in the regressions, a different set of poverty lines has no effect on the value and significance level of the estimates of non-geographic coefficients in the urban and rural regressions. But it has an impact on the value (but not the standard deviation) of the constant terms and the coefficients of the district dummies (Wodon, 1996). Holding the urban and rural poverty lines for the Dhaka district constant, we can compute for each district alternative poverty lines yielding zero district coefficients in the two regressions. Denoting by $Z_{U,Rk}$ the original poverty lines yielding the estimates of $\delta_{U,Rk}$ reported in Table 1, the alternative poverty lines are:

$$Z_{uk}{*}= Z_{Uk} /\exp(-\delta_{Uk}) \qquad (7)$$

$$Z_{rk}{*}= Z_{Rk} /\exp(-\delta_{Rk}) \qquad (8)$$

for urban and rural areas respectively of district k.

The implicit poverty lines computed using (7) and (8) turn out to be implausible. Because the conditional consumption tends to be higher in the Dhaka district than elsewhere (whether we consider urban or rural areas), the poverty lines in most other districts must fall to yield conditional measures of living standards similar to those existing in Dhaka. The implied differentials in poverty lines are too large to be believed. Consider urban areas. When we are using the initial poverty lines corresponding to the lower non-food allowance (described above) the decrease in the poverty lines of the non-Dhaka districts necessary for nullifying the coefficient estimates is so large that two thirds of the districts have negative non-food allowances if we keep the food component of the poverty lines unaltered. Even when we are using the initial poverty lines obtained with the larger non-food allowance—corresponding to the non-food consumption of the households spending the food poverty lines on food—the change in poverty lines needed to nullify the coefficient estimates are such that several of the districts would still need to have negative or zero non-food allowances. The geographic effects are too large to be attributed to measurement errors in the poverty lines.

3.3 Omitted variables

The geographic effects may also be due to omitted household variables which are correlated with geographic location. To test the robustness of the geographic effects to the specification of the model we searched for additional household variables which might affect consumption and be correlated with geographic location. The only major group of household characteristics available in the data sets which we did not use in equations (1)-(2) consists of housing attributes. These are almost certainly endogenous, though they may also be correlated with important omitted variables such as long-term wealth. We preferred to exclude housing attributes from our main regressions. However, for the purposes of this test, let us assume that the endogeneity problem is less severe than the omitted variables bias. For each household, we have information on the dwelling's wall and roof material, on the number of bedrooms and their size, and on its latrine and water systems.

Adding the housing characteristics did not result in any major difference in the estimates of the parameters of the district dummies. At the five percent level, the coefficient estimates of the district dummies obtained on adding the housing variables (a total of 23 dummies) differed significantly from the estimates reported in Table 1 for only 3 of the 17 urban areas, and 4 of the 17 rural areas. It remained true that we could safely reject the null that the coefficients on either the geographic or non-geographic variables were equal in urban and rural areas.

4 How much do geographic effects matter?

4.1 Decompositions

Mean real per capita consumption is much higher in urban than in rural areas. In 1991-92, urban households had on average a per capita consumption equal to one and a half times their poverty line, while the consumption of rural households barely matched their poverty line. Are these differences due to household characteristics or to geographic effects?

The observed urban-rural difference in mean log consumption can be written:

$$E[\log C_i \mid i \in U, X_i = X_U] - E[\log C_i \mid i \in R, X_i = X_R] =$$

$$(\alpha_U - \alpha_R) + (\beta_U' X_U - \beta_R' X_R) + \sum_k (s_{Uk}\delta_{Uk} - s_{Rk}\delta_{Rk}) \qquad (9)$$

where $X_{U,R}$ are the sample means for urban and rural areas respectively, and $s_{U,Rk}$ is the proportion of district k's households in each sector. Table 3 provides the results of the decomposition. The difference between the two constants is not significant. However, that does not mean that living in an urban or a rural area has no impact on a household's standard of living, holding other characteristics constant. This point can be seen by looking at the second term in the decomposition which represents the differential impact of all non-excluded and non-geographic variables in the two sectors. For each year, most of the urban-rural differential is due not only to higher education levels in the urban areas, but also to significantly higher returns to education there. The edge provided by education in urban areas is not compensated by higher land ownership and higher returns to land in rural areas. The lower returns to land (and higher returns to education) in urban areas are consistent with the stylized fact that many rural households migrating to cities are landless or near landless.

The third and last term in the decomposition is close to zero for both years. This term indicates that on average and controlling for other characteristics, the gap between the urban areas of Dhaka and all the other urban areas ($\sum_k s_{Uk} \delta_{Uk}$) is of the same order of magnitude as the gap between the rural areas of Dhaka and all the other rural areas ($\sum_k s_{Rk} \delta_{Rk}$).

To compare living standards in two urban or two rural districts at one point of time while controlling for other household characteristics, we may simply compare the coefficients of the district dummies. In 1991-92, all but one of the urban and all but two of the rural district coefficient estimates are negative. Households living in the capital district of Dhaka appear to be better off than their urban or rural counterparts in other districts after controlling for the measured non-geographic characteristics. The comparative edge of the households in the Dhaka district makes sense since Dhaka City is the capital and it is better endowed than other areas. It is also consistent with the large migration to the capital which resulted in an annual rate of growth between 1981 and 1991 for the Standard Metropolitan Areas of Dhaka of 7.3 percent, as compared to 4.1 percent for the Chittagong SMA and 4.5 percent for the Khulna SMA (the Rasjhahi SMA grew at a rate of 8.0 percent). Note also that spatial effects are not limited to differences between Dhaka and the other districts. Many district coefficients are significantly different from each other.

What about sectoral effects within districts? Even if there are no pure sector-wide effects (appearing through the constants), there may be sectoral effects within districts. Holding everything else constant, we may have a significant difference between the urban and rural households of a given district even if this difference does not hold when we are comparing all urban and all rural districts at once. And we may as before also have indirect sectoral effects working through differential returns to household characteristics between urban and rural areas.

To compare the conditional mean consumption of the urban and rural areas of a given district, we cannot rely only upon the difference between the coefficients of the district dummies in the urban and rural regressions. First, for the non-geographic variables, we need to take into account the different returns to these variables in urban and rural areas. Second, for the geographic variables, observing a statistically significant difference between the urban (δ_{Uj}) and rural (δ_{Rj}) coefficients of district j in the two regressions does not mean that the impact of living in that district will vary between urban and rural areas. The district effects captured by the dummy coefficients are relative to the excluded dummy in both regressions. If, in the excluded district of Dhaka, there is a difference between the living standards of urban and rural households after controlling for other characteristics (this difference will show up in the constant terms), then even if there is no difference in the conditional living standards of urban and rural households in other districts, we may still observe significant differences in the urban and rural dummy coefficients of these other districts. Third, in asking how conditional standards of living differ between the rural and urban areas of a given district, we should not condition on the sample mean characteristics of the households living in urban and rural areas because these sample means are not equal, and hence we are not holding non-geographic characteristics constant.

A better approach is to compute the expected gain in consumption from living in urban areas of a given district over rural areas, given that the household has the national mean $\dot{X}_N$ (say).

For the j'th district, this is given by:

$$E[\log C_i \mid i \in U, D_i = D^j, X_i = X_N] - E[\log C_i \mid i \in R, D_i = D^j, X_i = X_N] =$$

$$(\alpha_U - \alpha_R) + (\beta_U' - \beta_R')X_N + (\delta_{Uj} - \delta_{Rj}) \qquad (10)$$

where D^j denotes the m-vector with 1 as the j'th element and 0 otherwise. The first two terms on the right hand side are the same for all districts. The first term is the same as that of equation (9). It represents the impact of unexplained sector-wide and excluded dummy differences between urban and rural areas. The second term represents the impact of differential returns to household characteristics in urban and rural areas. The term is the same as that of equation (9), except for the fact that we conditioned on national sample means rather than on urban and rural means. When conditioning on national means, we "correct" the expected consumptions obtained when conditioning on urban and rural means by adding $\beta_U'(X_N - X_U)$ to the urban consumption measures and $\beta_R'(X_N - X_R)$ to the rural measures. Because urban households tend to have characteristics (less children, better education, better jobs) which are more favorable than the national average, conditioning on national means results for them in a lower estimate of their log consumption than would have been obtained with urban means. The reverse applies to rural households for which conditional log consumption using national means is higher than when using rural means.[10]

In equation (10), the sum of the two first terms (0.21 in 1988-89 and 0.18 in 1991-92) accounts for the difference between the conditional consumption of households living in the urban and rural areas of the Dhaka district when conditioning on national means. For the other districts,

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[10] The terms $\beta_U(X_N - X_U)$ and $\beta_R(X_N - X_R)$ turn out to be equal respectively to -0.13 and 0.04 for both survey years. The equality for both years of the urban as well as the rural corrections in both years suggests a stability over time in the differences between each sector and the national average when the benefits of these differences are computed using the year's returns.

the differences between conditional urban and rural living standards may be greater or smaller than those observed in Dhaka due to the third term (δ_{Uj} - δ_{Rj}). For 1991-92, as can be computed from the coefficient estimates given in Table 1, (δ_{Uj} - δ_{Rj}) is close to zero (i.e. it varies between -0.06 and 0.04) for half of the districts. In this first group of districts, the differences in expected log consumptions between urban and rural areas are as pronounced as those existing in the Dhaka district. However, for the other half of the districts, (δ_{Uj} - δ_{Rj}) is negative and large (i.e. it varies between -0.17 and -0.46), suggesting few overall differences in expected log real consumptions between urban and rural areas once we control not only for household characteristics, but also for the sectoral geographic effects within districts. This differentiated pattern between the two groups of districts is relatively stable over time as the correlation between the sectoral geographic effects (δ_{Uj} - δ_{Rj}) of the two years is large and positive (0.84).

The differentiated patterns in sectoral effects within districts are not random. It is striking that the urban-rural conditional differences appear to follow divisional patterns (each administrative division consists of several contiguous districts). Most districts in the Rajshahi division (Rajshahi, Rangpur, Pabna, and Bogra) and in the Dhaka division (Dhaka, Mymensingh, and Faridpur) have large differences in standards of living between urban and rural areas after controlling for household and district characteristics (the only two exceptions are Tangail/Jamalpur in the Dhaka division and Dinajpur in the Rajshahi division). In the other divisions, urban and rural standards of living tend to be similar once we control for household and district characteristics (the two exceptions are the Khulna district for which urban households are better off and Noakhali for which rural households are better off). These patterns match the migration observed by the BBS (1995a: 46, Table 3.5) between administrative divisions. The BBS estimated that the number of life time net migrants for

1991 to be positive for the Dhaka (642,000 net migrants) and Rajshahi (422,000) divisions, and negative for the Barisal (-481,000), Chittagong (-285,000) and Khulna (-298,000) divisions. Thus our results are consistent with the plausible assumption that, given their characteristics, people migrate to areas where they can obtain higher consumption.

4.2 *Measures of mean consumption*

The relative importance of geographic effects can also be assessed by comparing the actual measures of consumption with simulated measures in which suitable controls are applied, so as to isolate the pure effects of geographic variation. Two sets of conditional simulated measures of consumption for the 34 geographic locations can be computed.

The first set of measures isolates the purely geographic effects by controlling for all the non-geographic characteristics; this is termed the geographic profile of living standards. It is obtained by using the parameter estimates of the two regressions to estimate for the urban and rural areas of each district the consumption of a household with the national mean characteristics, denoted X_N. If consumption was fully determined by the observed non-geographic household characteristics, then the coefficients of the district dummies would be zero in both regressions, the returns to non-geographic characteristics (both those included in the regression and those excluded as reference dummies) would be the same in urban and rural sectors, and the two constant terms would be the same. Then the conditional measures of consumption would be the same everywhere. Put differently, the difference between the geographic and unconditional profiles reflects the impact of non-geographic effects on standards of living.

The second set of measures isolates the effects of the non-geographic characteristics, by controlling for the geographic differences. We call this the concentration profile (because it reflects the spatial concentration of non-geographic characteristics). In this case only differences in geographic characteristics come into play when we compare these conditional measures to the actual (unconditional) ones. Computing the mean parameter estimates $\alpha_N = s_U(\alpha_N + \sum_k \delta_{Rk}) + s_R (\alpha_R + \sum_k \delta_{Rk})$ and $\beta_N = s_U\beta_R + s_R\beta_R$ where s_U and s_R are the urban and rural household shares, we can define the measure of consumption for the urban areas in district j conditional on geographic characteristics as $\log C^j = \alpha_N + \beta_N' X^j_U$ where X^j_U represents the sample mean non-geographic characteristics of the households living in urban areas of district j. Doing the same for all urban and rural areas, we obtain the concentration profile. By seeing how much these simulated measures vary between the 34 urban and rural areas, we can assess the contribution of the concentration effects to the differences in living standards.[11]

Table 4 provides estimates of the actual (unconditional) and the two simulated profiles for mean real consumption by area.[12] Consider first the pure geographic profile obtained by conditioning on X_N. Urban conditional measures of consumption tend to be larger than rural ones,

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[11] We can ignore the residuals in the geographic and concentration conditional profiles since the residuals must sum to zero in each district due to the inclusion of dummy district variables in the regressions (for if the mean residuals were not zero in a given district, a better fit could be obtained in the regression through a revised estimate for the coefficient of the corresponding dummy). Therefore, whether the residuals are due to omitted individual characteristics (in which case they should be included in the concentration profile) or to omitted area characteristics (in which case they should be included in the geographic profile), their mean vanishes in each district so that they do not affect the mean consumption level or probability of being poor of our representative households.

[12] Note that the weighted sum of the conditional urban (or rural) log real consumptions by district when conditioning on non-geographic characteristics need not be equal to the unconditional log real consumption at the mean of the urban sample as a whole. To see this, denote as before by s_{Uj} the household share of district j among all urban areas. In logarithms, the household share weighted sum of the conditional real per capita consumption levels by district is $\sum_j s_{Uj} E[\log C_i \mid i \in U, D_i = D^j, X_i = X_U] = \sum_j s_{Uj} [\alpha_U + \beta_U X_U + \delta_{Uj}]$, which is equal to the corresponding unconditional value obtained by the properties of linear unbiased regressions as $E[\log C_i \mid i \in U, X_i = X_U] = \alpha_U + \beta_U X_U + \sum_j s_{Uj} \delta_{Uj}$.) On the other hand, in terms of log real consumptions, $\sum_j s_{Uj} \exp\{E[\log C_i \mid i \in U, D_i = D^j, X_i = X_U]\}$ is not equal to $\exp\{E[\log C_i \mid i \in U, X_i = X_U]\}$, simply because the exponential operator is not linear.

in part because of the difference in constants between the urban and rural regressions ($\alpha_U - \alpha_R = 0.26$ in 1991-92). For most urban areas the geographic conditional consumptions are lower than the unconditional consumptions due to the negative urban correction imposed when controlling for the mean household characteristics, set at the national mean. As noted earlier, urban households tend to have more favorable characteristics than rural households, which results for them in conditional levels of consumption below what would have been obtained using urban means. The reverse holds for rural consumptions. Nevertheless, there is a large positive correlation between the geographic and the unconditional profiles (the correlations are 0.84, 0.81 and 0.98 for all areas, the urban areas, and the rural areas respectively in 1991-92).

Consider next the concentration profile obtained by using the weighted means of the urban and rural parameter estimates. Urban areas are still for the most part better off than rural ones, but this time, it is because households living in urban districts tend to have those non-geographic characteristics which raise living standards. The conditional concentration consumption measures for urban areas are still below the unconditional ones, but this time because returns to characteristics tend to be higher in urban areas than nationally (the reverse is true for rural areas). The correlation between the concentration and actual profiles is lower (0.47, 0.20 and 0.19 for all areas, the urban areas, and the rural areas respectively in 1991-92) than between the geographic and actual profiles.

In Figure 1, there are 34 points corresponding to the urban and rural areas of the 17 districts. The districts have been ranked on the horizontal axis by unconditional consumption (in proportion to the poverty line). The 45 degree line thus represents the unconditional profile. The two dashed locii represent the geographic and concentration profiles. The overall positive slope

(0.70) of the regression of the geographic on the unconditional profile reflects the fact that geographic effects account for a large part of the unconditional differences in consumption between areas (i.e., the geographic regression is close to the 45 degree line). Controlling for non-geographic characteristics reduces the welfare gaps between districts, but not by much. There is also a positive correlation between the concentration and actual profiles, but the relationship is weaker, as indicated by the smaller slope of the concentration regression (0.21).

Another summary statistic that shows clearly the relative importance of geographic versus non-geographic effects in determining consumption is the spatial variance of the simulated geographic and concentration consumptions divided by the spatial variance of the actual values. Pooling urban and rural areas, the variance of the geographic profile accounts for 80 percent of the variance of the actual profile in 1991-92, while the variance of the concentration profile accounts for 59 percent of the unconditional variance.

If we observe genuine geographic effects, these should be stable over relatively short periods of time. One way to check the stability of geographic effects over time consists in computing the correlation between the district-level dummy coefficients of the two years. This correlation is large and positive for both the urban (0.75) and the rural (0.84) regressions. A more comprehensive approach taking into account not only district-level but also other types of geographic effects (sector-wide effects and sectoral effects within districts) is to compare the consumption levels of all urban and rural areas over time while holding household characteristics constant at (say) the national 1991-92 sample means X_N. Table 4 also gives the conditional geographic profile for 1988-89 using the national 1991-92 means. The correlations between the conditional geographic profiles for the two years are positive and large as expected (0.83, 0.88 and

0.83 for all areas, the urban areas, and the rural areas).

4.3 Poverty measures

For targeting purposes, comparisons of poverty rather than mean consumption are often relied upon in order to place more emphasis on less favored households. From the urban and rural regressions, we can estimate probabilities of being poor. Since C_i is nominal consumption deflated by the poverty line, a negative (positive) value of its log means that the household is poor (not poor). Assuming normally distributed errors, and conditioning on national sample means for 1991-92, the geographic poverty profile is based on the conditional probabilities of being poor for household living in district j:

$$\mathrm{Prob}[\log C_i<0 \mid i \in U, D_i=D^j, X_i=X_N]=\Phi[-(\alpha_U + \beta_U' X_N + \delta_{Uj})/\sigma_U] \quad (11)$$

$$\mathrm{Prob}[\log C_i<0 \mid i \in R, D_i=D^j, X_i=X_N]=\Phi[-(\alpha_R + \beta_R' X_N + \delta_{Rj})/\sigma_R] \quad (12)$$

for urban and rural areas respectively, where σ_U and σ_R are the standard deviations of the errors in the urban and rural regressions and Φ is the cumulative density of the standard normal.[13] For the concentration profile, we condition on the weighted means of the urban and rural parameters.

Table 5 provides the unconditional, concentration, and geographic profiles for the percentage of people in each area deemed to live in households with mean consumption below the poverty line (the "headcount index" of poverty). Most urban areas have lower measures of poverty than rural areas. Note that the geographic headcounts are based on national rather than urban means for non-geographic households characteristics. This tends to increase their headcount

[13] At the aggregate level, the use of the headcount indices does not maintain the property that unconditional and conditional measures of welfare are equal. Moreover, because of the nonlinearity of the normal cumulative density function, we cannot provide linear decompositions of the differences between headcount indices. Yet, we can still compare the conditional and unconditional headcount indices obtained by district at one point of time, as well as the conditional indices obtained over time.

indices when compared to the unconditional benchmark. By contrast, the rural geographic headcounts tend to be lower than the unconditional ones. The concentration headcounts for urban areas are also higher than the unconditional ones because the national mean returns to characteristics tend to be lower than the urban returns. The reverse applies to the rural concentration headcounts. As for consumption, the correlation between the geographic and unconditional profiles is larger than that between the concentration and unconditional profiles. In fact, the geographic poverty profile is very similar to the actual (unconditional) one. For example, the poorest area in 1991-92 (rural Rangpur) is also the poorest when one controls for non-geographic household characteristics (65% are poor unconditionally; 62% with the controls). And the least poor area (rural Sylhet, with a headcount index of 11% in 1991-92) is also the least poor with the controls (9%). When urban and rural areas are pooled, the variance of the geographic profile is equal to that of the unconditional profile, while the variance of the concentration profile is less than half that of the unconditional profile.

In Figure 2, the areas have been ranked by the unconditional headcount index for 1991-92. With a slope of 0.86, the dashed line for the regression of the geographic poverty measures on the unconditional poverty measures is close to the slope of the 45 degree line representing the unconditional profile. The slope of the concentration regression is lower, at 0.21.

5 Conclusion

We find significant and sizable geographic effects on living standards in Bangladesh, after controlling for a range of observable non-geographic characteristics. Poor areas are not just poor because households with readily observable attributes which foster poverty are geographically concentrated. There appear to be sizable spatial differences in the returns to given household characteristics. And there are independent spatial differences not accountable to any obvious differences in observable household characteristics or to differences in the returns to those characteristics. These effects could arise either from restrictions on mobility or from omitted, and spatially correlated, heterogeneity in household characteristics. The geographic effects accord with independent evidence on migration patterns.

Our results reinforce the case for anti-poverty programs targeted to poor areas even in an economy with few obvious impediments to mobility. They do not, however, imply that public investment in poor areas is the best option–there may also be scope for reducing migration costs, such as by providing labor market information or helping with set-up costs. Nor do our results tell us what aspects of poor areas are giving rise to poverty; is it lack of physical infrastructure, or something else, such as poor schools, or heterogeneity in omitted household characteristics? Further work is needed to determine what specific forms poor-area policies should take, and whether they are cost effective relative to alternative non-geographic policies. However, our results do suggest that there is a compelling case for further work on these issues.

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Table 1: Regressions for log real consumption

	1988-89				1991-92			
	Urban		Rural		Urban		Rural	
	Coeff.	St. Er.	Coeff.	St. Er.	Coeff.	St. Er.	Coeff.	St. Er.
Constant	0.43*	0.12	0.17*	0.08	0.33*	0.12	0.19*	0.06
District								
Mymensingh	-0.26*	0.05	-0.12*	0.03	-0.20*	0.04	-0.21*	0.03
Faridpur	-0.34*	0.04	-0.25*	0.03	-0.36*	0.05	-0.31*	0.03
Tangail/Jamalpur	-0.63*	0.08	-0.20*	0.04	-0.56*	0.09	-0.31*	0.03
Chittagong	0.01	0.03	0.01	0.04	-0.06*	0.03	0.13*	0.03
Comilla	-0.21*	0.04	-0.11*	0.03	-0.30*	0.04	-0.04	0.03
Sylhet	0.12	0.09	0.18*	0.03	0.04	0.07	0.21*	0.03
Noakhali	-0.49*	0.06	-0.09*	0.04	-0.51*	0.09	-0.04	0.03
Khulna	-0.13*	0.03	-0.09*	0.04	-0.20*	0.03	-0.17*	0.03
Jessore	-0.17*	0.05	-0.07*	0.03	-0.23*	0.05	-0.02	0.03
Barisal/Patuakhali	-0.37*	0.04	-0.15*	0.03	-0.39*	0.05	-0.22*	0.03
Kushtia	-0.23*	0.06	-0.17*	0.04	-0.33*	0.07	-0.10*	0.04
Rajshahi	-0.17*	0.04	-0.06	0.03	-0.28*	0.04	-0.25*	0.03
Rangpur	-0.19*	0.04	-0.13*	0.03	-0.28*	0.05	-0.32*	0.03
Pabna	-0.09	0.05	-0.20*	0.03	-0.27*	0.06	-0.21*	0.03
Dinajpur	-0.32*	0.03	-0.21*	0.03	-0.33*	0.05	-0.16*	0.03
Bogra	-0.42*	0.08	-0.08*	0.04	-0.18	0.09	-0.21*	0.03
Demographics								
Number of babies	-0.16*	0.03	-0.20*	0.02	-0.25*	0.02	-0.20*	0.01
Number of babies squared	0.01	0.01	0.02*	0.01	0.04*	0.01	0.03*	0.00
Number of children	-0.20*	0.02	-0.16*	0.01	-0.16*	0.02	-0.17*	0.01
Number of children squared	0.03*	0.00	0.02*	0.00	0.02*	0.00	0.02*	0.00
Number of adults	-0.15*	0.02	-0.10*	0.02	-0.10*	0.02	-0.11*	0.01
Number of adults squared	0.01*	0.00	0.01*	0.00	0.01*	0.00	0.01*	0.00
Sex of the head	-0.06	0.07	-0.02	0.05	0.00	0.06	-0.07	0.04
No spouse, married	0.35*	0.06	0.05	0.05	0.19*	0.05	0.20*	0.03
No spouse, single	0.27*	0.05	0.09*	0.04	0.04	0.06	0.11*	0.03
No spouse, divorced/widowed	0.01	0.06	-0.03	0.05	-0.04	0.07	-0.01	-0.04
Age of the head	0.01	0.00	0.01*	0.00	0.00	0.00	0.00	0.00
Age of the head squared	0.00	0.00	0.00*	0.00	0.00	0.00	0.00	0.00
Non Muslim	0.01	0.03	0.01	0.02	-0.04	0.03	-0.05*	0.02

Education of Head								
Below class 5	0.11*	0.03	0.11*	0.02	0.15*	0.03	0.07*	0.01
Class 5	0.20*	0.03	0.22*	0.02	0.16*	0.03	0.10*	0.02
Class 6 to 9	0.39*	0.04	0.24*	0.04	0.28*	0.03	0.15*	0.02
Higher level	0.56*	0.06	0.48*	0.07	0.42*	0.04	0.22*	0.03
Education of Spouse								
Below class 5	0.03	0.03	0.04*	0.02	0.05	0.03	0.05*	0.02
Class 5	0.16*	0.03	0.10*	0.04	0.09*	0.03	0.12*	0.02
Class 6 to 9	0.32*	0.05	0.06	0.10	0.15*	0.03	0.17*	0.03
Higher level	0.42*	0.10	0.52*	0.22	0.39*	0.04	0.26*	0.06
Education Differential								
One level higher	0.13*	0.03	0.10*	0.02	0.04	0.03	0.09*	0.02
Two levels higher	0.26*	0.04	0.15*	0.03	0.12*	0.04	0.14*	0.02
Three levels higher	0.31*	0.06	0.26*	0.06	0.13*	0.05	0.17*	0.03
Four/more levels higher	0.35*	0.10	0.03	0.05	0.37*	0.08	0.12*	0.04
Land Ownership								
0.05 to 0.49 acres	0.09*	0.02	0.08*	0.02	0.08*	0.02	0.08*	0.02
0.50 to 1.49 acres	0.07*	0.03	0.12*	0.02	0.07*	0.03	0.17*	0.02
1.50 to 2.49 acres	0.15*	0.04	0.21*	0.03	0.09*	0.04	0.27*	0.02
2.50 acres or more	0.20*	0.03	0.38*	0.03	0.25*	0.04	0.41*	0.02
Main Occupation								
Agricultural worker with land	0.12	0.08	0.09*	0.03	0.13	0.10	0.09*	0.02
Fisheries/forestry/live stock worker	0.13	0.07	0.16*	0.03	0.31*	0.10	0.18*	0.03
Tenant farmer	0.12*	0.04	0.17*	0.02	0.27*	0.07	0.18*	0.02
Owner farmer	0.22*	0.07	0.13*	0.02	0.33*	0.07	0.17*	0.02
Servant, day-laborer	0.14*	0.05	0.08*	0.03	0.16*	0.05	0.09*	0.03
Transportation, communicat. worker	0.06	0.04	0.21*	0.03	0.25*	0.05	0.19*	0.03
Salesman, service, broker, middlem.	0.14*	0.04	0.20*	0.03	0.20*	0.05	0.19*	0.03
Factory worker, artisan	0.21*	0.04	0.20*	0.03	0.30*	0.06	0.15*	0.03
Petty trader, small businessman	0.32*	0.04	0.23*	0.03	0.36*	0.05	0.25*	0.02
Executive, official, profess., teacher	0.16*	0.04	0.19*	0.04	0.29*	0.05	0.26*	0.03
Retired person, student, non working	0.11*	0.06	0.11*	0.04	0.34*	0.06	0.09*	0.03

Source: Authors' computations from HES unit level data. Standard errors corrected for heteroscedasticity. Number of observations in 1988-89: 1856 urban and 3770 rural. R^2= 0.59 urban and 0.41 rural. Number of observations in 1991-92: 1908 urban and 3817 rural. R^2= 0.55 urban and 0.50 rural. The symbol * indicates significance at the 5% level of confidence. The excluded dummies are the Dhaka district, the married head with a spouse, the male household head, the Muslim religion, the illiterate head, the illiterate spouse, the zero education differential between other members and the maximum educational level between the head and the spouse (or the head if he has no spouse), the landless household, and the landless agricultural worker.

Table 2: Test of equality between the urban and rural regressions (1991-92)

	RSS	Number of restrictions	F value	F test
Unrestricted model	626.21	-	-	-
Test of equality of coefficients				
All variables	662.02	57	5.63	Rejected 1 %
Constant	626.34	1	1.24	Accepted
Non-geographic variables	642.21	40	3.58	Rejected 1 %
Household size variables	627.57	6	2.03	Accepted
Other demographics/religion	626.56	7	0.45	Accepted
Education variables	632.68	12	4.83	Rejected 1 %
Land variables	629.41	4	7.18	Rejected 1 %
Occupation variables	629.81	11	2.94	Rejected 1 %
Geographic variables	636.94	16	6.01	Rejected 1 %

Source: Authors' computations from HES unit level data based on 5725 observations and 113 variables in the unrestricted model.

Table 3: Decomposition by sector

	Urban areas		Rural areas	
	1988-89	1991-92	1988-89	1991-92
Log mean consumption	0.47	0.41	0.10	0.05
Constant	0.43	0.33	0.17	0.19
Geographic variables	-0.11	-0.14	-0.10	-0.14
Non-geographic variables	0.15	0.22	0.02	0.00
Household size variables	-0.64	-0.52	-0.53	-0.53
Other demographics/religion	0.24	0.09	0.16	0.13
Education variables	0.31	0.33	0.12	0.12
Land variables	0.06	0.05	0.15	0.15
Occupation variables	0.17	0.27	0.12	0.13

Source: Authors' computations from HES unit level data. Numbers may not add up due to rounding.

Table 4: Consumption by district and by urban/rural areas

Consumption normalized by regional poverty lines	Geographic profile (using 1991-92 national means)				Concentration profile (using 1991-92 mean parameters)				Unconditional profile			
	1988-89		1991-92		1988-89		1991-92		1988-89		1991-92	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
District												
Dhaka	1.76	1.37	1.52	1.25	1.21	1.10	1.33	1.16	1.74	1.22	1.77	1.21
Mymensingh	1.36	1.21	1.25	1.01	1.19	1.13	1.26	1.16	1.42	1.09	1.37	0.99
Faridpur	1.26	1.07	1.06	0.91	1.14	1.07	1.17	1.15	1.15	0.93	1.03	0.88
Tangail/Jamalpur	0.94	1.12	0.87	0.92	1.13	1.07	1.29	1.15	0.78	0.97	0.94	0.88
Chittagong	1.78	1.39	1.43	1.42	1.22	1.07	1.29	1.11	1.89	1.23	1.59	1.30
Comilla	1.42	1.23	1.13	1.20	1.23	1.11	1.25	1.17	1.56	1.11	1.25	1.16
Sylhet	1.99	1.64	1.58	1.54	1.12	1.06	1.08	1.15	1.79	1.40	1.47	1.49
Noakhali	1.08	1.26	0.92	1.20	1.18	1.09	1.43	1.17	1.03	1.08	1.16	1.16
Khulna	1.54	1.26	1.25	1.05	1.26	1.12	1.39	1.21	1.57	1.14	1.49	1.06
Jessore	1.49	1.28	1.21	1.22	1.23	1.11	1.34	1.16	1.48	1.13	1.37	1.19
Barisal/Patuakhali	1.21	1.18	1.03	1.01	1.29	1.14	1.41	1.19	1.21	1.08	1.23	1.00
Kushtia	1.40	1.15	1.09	1.12	1.19	1.07	1.31	1.19	1.39	0.98	1.22	1.13
Rajshahi	1.49	1.29	1.14	0.97	1.32	1.13	1.40	1.16	1.69	1.18	1.45	0.94
Rangpur	1.46	1.20	1.15	0.91	1.23	1.10	1.28	1.11	1.51	1.07	1.28	0.84
Pabna	1.61	1.12	1.16	1.01	1.17	1.02	1.30	1.08	1.61	0.93	1.31	0.91
Dinajpur	1.28	1.11	1.09	1.07	1.23	1.13	1.25	1.11	1.24	1.03	1.15	0.99
Bogra	1.16	1.27	1.26	1.01	1.02	1.08	1.07	1.17	1.48	1.11	1.12	0.99

Source: Authors' computations from HES unit level data. A value of 1 indicates that consumption is at the poverty line for that district.

Table 5: Headcount index of poverty by district and by urban/rural areas

Percentage of households below the poverty line	Geographic profile (using 1991-92 national means)				Concentration profile (using 1991-92 mean parameters)				Unconditional profile			
	1988-89		1991-92		1988-89		1991-92		1988-89		1991-92	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
District												
Dhaka	6.01	18.92	12.50	24.23	44.33	54.57	34.73	48.44	15.86	33.82	13.47	39.48
Mymensingh	19.78	29.39	27.13	48.58	45.88	52.32	40.26	48.66	30.00	43.04	32.89	52.19
Faridpur	26.41	42.73	43.60	61.03	50.80	57.65	48.56	49.88	41.27	62.21	51.56	64.25
Tangail/Jamalpur	56.60	37.19	65.11	60.41	51.84	57.55	37.35	49.75	75.00	55.56	50.00	58.58
Chittagong	5.67	17.87	16.16	13.61	43.39	57.65	38.03	55.02	9.67	27.75	16.97	20.00
Comilla	16.60	28.19	36.77	28.31	42.38	53.62	40.56	48.04	26.32	38.26	37.50	34.80
Sylhet	2.96	8.29	10.46	8.85	52.94	58.78	57.09	49.57	10.71	20.60	12.50	10.78
Noakhali	41.91	26.25	59.39	28.70	47.17	56.35	27.78	47.80	25.00	51.14	37.50	37.36
Khulna	11.62	26.17	27.09	43.41	40.28	53.10	30.41	43.87	23.95	41.95	27.08	48.57
Jessore	13.57	24.48	30.10	26.37	42.72	53.75	33.91	48.71	23.44	38.22	21.88	35.79
Barisal/Patuakhali	30.01	32.41	47.29	49.23	37.32	51.33	28.68	45.73	29.03	48.76	40.63	52.49
Kushtia	17.62	34.44	40.27	35.62	46.52	57.84	36.06	45.63	26.09	57.45	34.38	38.54
Rajshahi	13.69	23.93	35.59	53.53	35.53	52.37	29.30	49.25	14.10	40.30	18.75	55.35
Rangpur	15.00	30.55	34.83	62.00	42.48	54.95	38.52	54.63	15.87	46.39	28.13	65.30
Pabna	9.63	37.28	34.18	48.22	48.22	62.91	36.77	58.19	12.50	54.69	27.91	62.50
Dinajpur	25.11	38.28	40.84	41.97	42.49	51.60	41.40	54.02	32.81	46.86	37.10	55.11
Bogra	34.50	25.16	25.99	48.42	62.62	56.71	58.14	48.21	62.50	41.13	37.50	51.75

Source: Authors' computations from HES unit level data. A headcount of 6.01 indicates that 6.01% of households are poor in that district.

FIGURE 1: GEOGRAPHIC AND CONCENTRATION PROFILES FOR CONSUMPTION

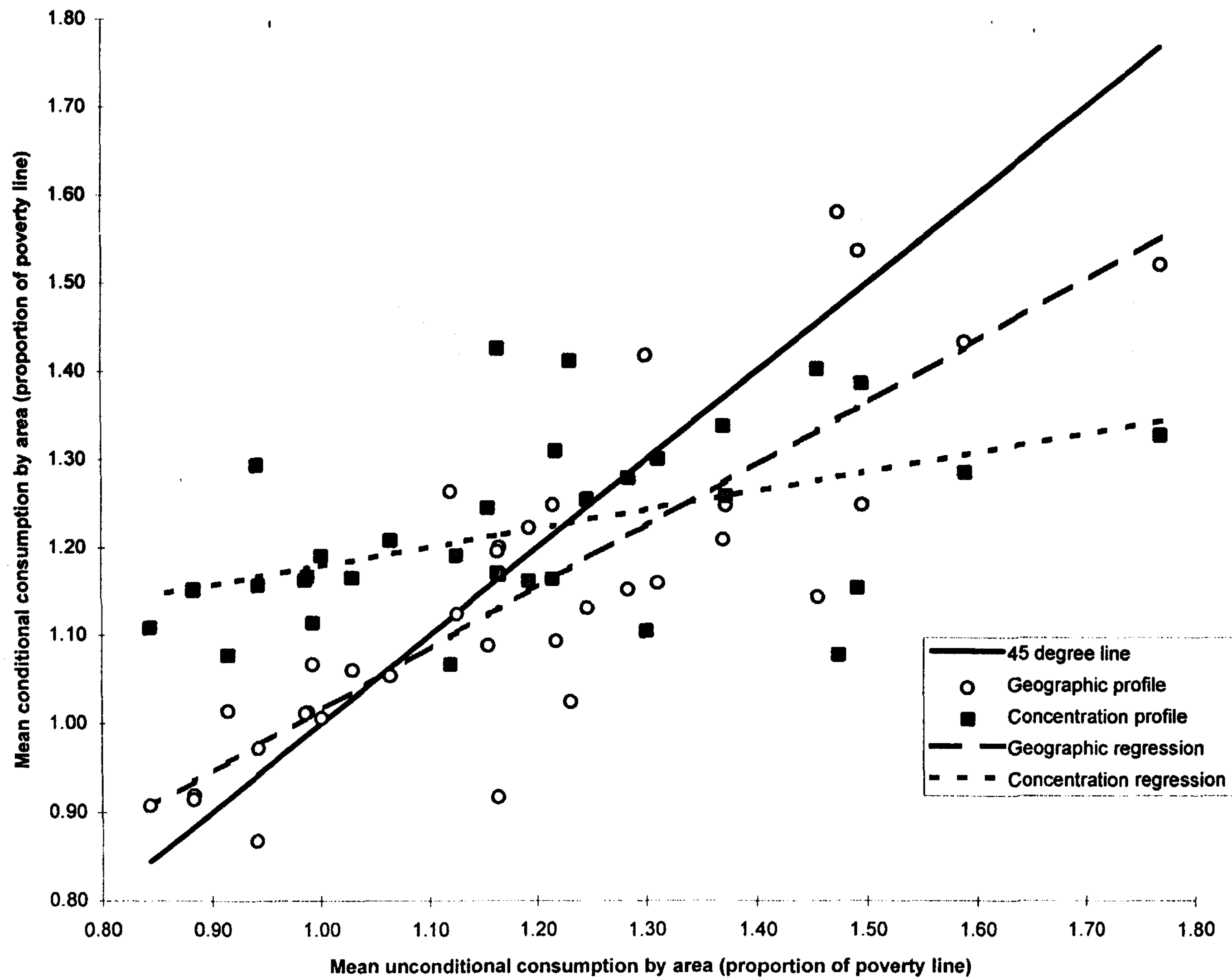
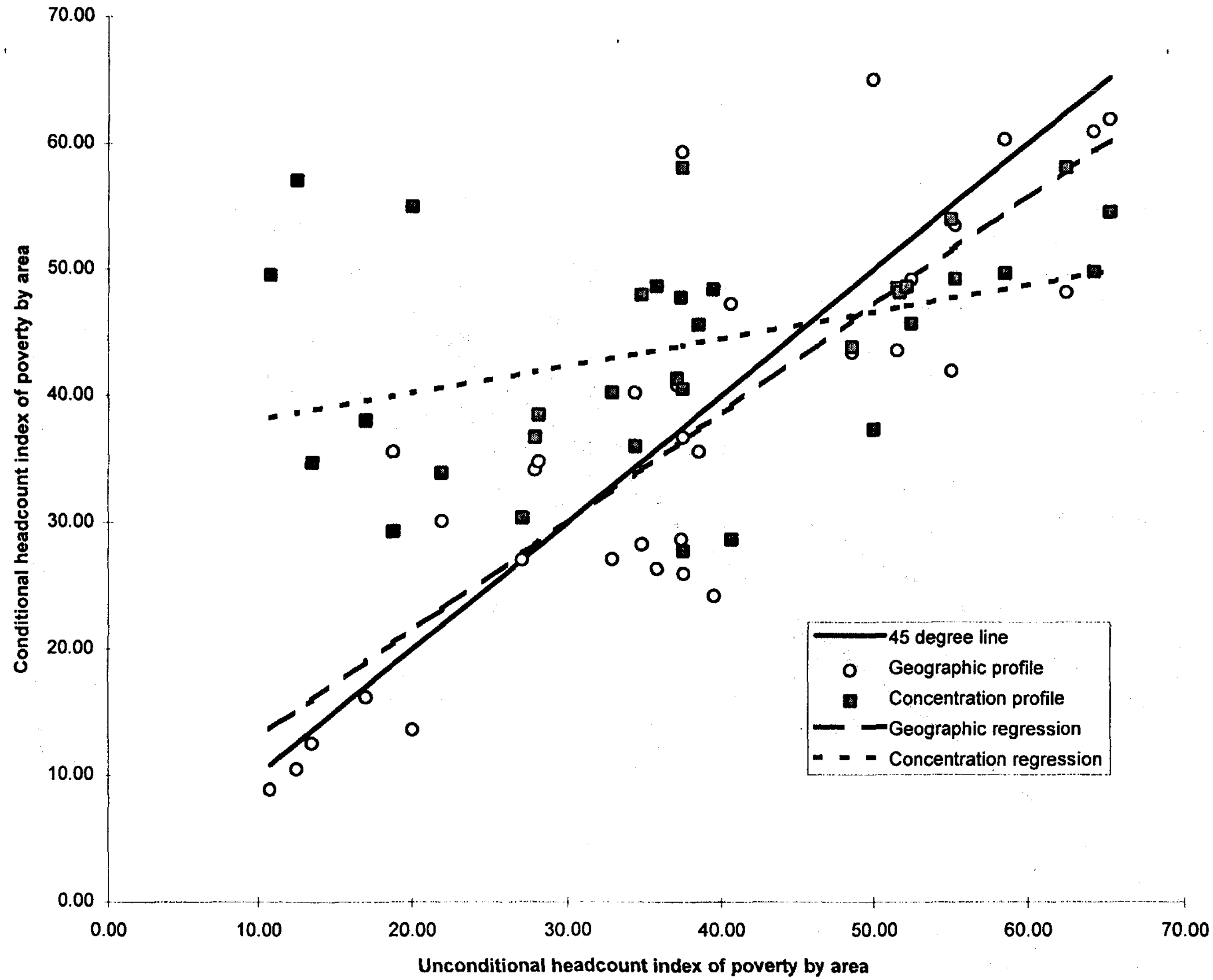


FIGURE 2: GEOGRAPHIC AND CONCENTRATION PROFILES FOR POVERTY



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